IBN HALDUN UNIVERSITY
SCHOOL OF GRADUATE STUDIES
DEPARTMENT OF ECONOMICS

MASTER THESIS

THE EFFECTS OF COVID-19 PANDEMIC ON THE VOLATILITIES OF THE DYNAMICS OF BITCOIN AND GOLD

MOHAMMED MUSAH

THESIS SUPERVISOR

ASST. PROF. ASAD UL ISLAM KHAN

ISTANBUL, 2022

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by

MOHAMMED MUSAH

A thesis submitted to the School of Graduate Studies in partial fulfilment of the requirements for the degree of Master of Arts in Economics

THESIS SUPERVISOR

ASST. PROF. ASAD UL ISLAM KHAN

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APPROVAL PAGE

This is to certify that we have read this thesis and that, in our opinion, it is fully adequate, in scope and quality, as a thesis for the degree of Master of Arts in Economics.

Thesis Jury Members

Title - Name Surname	Opinion	Signature
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This is to confirm that this thesis complies with all the standards set by the School of Graduate Studies of Ibn Haldun University.

Date of Submission   Seal/Signature

ACADEMIC HONESTY ATTESTATION

I hereby declare that all information in this document has been obtained and presented in accordance with academic rules and ethical conduct. I also declare that, as required by these rules and conduct, I have fully cited and referenced all material and results that are not original to this work.

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ÖZ

COVİD-19 PANDEMİSİNİN BİTCOİN VE ALTIN DİNAMİĞİNİN VOLATİLİTELERİ ÜZERİNDEKİ ETKİLERİ

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Piyasalar, uluslar ve ekonomiler arasındaki bağlantıların her zamankinden daha güçlü hale geldiği bu ileri teknolojik çağda sağlık krizinin ortaya çıkması, covid-19, hem fiziksel hem de dijital finans piyasaları covid-19 pandemisinin şokundan hızla etkilendi. Çin finans piyasası covid-19 pandemisinin ilk sonuçlarını yaşadı, Çin borsalarındaki şoklar bitcoin, altın ve dünyadaki diğerleri gibi diğer finans piyasalarına da sıçradı. Bu tez, covid-19'un kripto para piyasasında bitcoin ve değerli metaller piyasasında altının dinamiklerinin oynaklıkları üzerindeki etkisine odaklanmaktadır. Altının ve bitcoin, her iki varlığın da dünya çapında çevrimiçi olarak alınıp satılabildiği bir çevrimçi platformu vardır, ancak altın fiziksel olarak çıkarıldığından ve aynı zamanda birçok fiziksel yolla kullanıldığından fiziksel bir forma sahiptir, oysa bitcoin dijital olarak üretildiğinden fiziksel bir forma sahip değildir ve herhangi bir fiziksel biçimde kullanılamaz bu makale, bu finansal varlıklar arasındaki bu benzerlik ve farklılıkların, covid-19 krizinin ilgili piyasaları nasıl etkilediği konusunda önemli roller oynadığını tartışmaktadır. Araştırma, ARMA'yı ortalama denklem olarak kullanarak GARCH modelini kullanıyor ve günlük bitcoin fiyatları ve hacimleri, altın fiyatları ve günlük verilerini kullanarak Covid-19'un sağlık krizinin bitcoin ve altın fiyat getirilerinin oynaklıkları ve hacim getirileri üzerindeki etkisini inceliyor. Tahminin ampirik sonuçları, covid-19'un oynaklıkları hem bitcoin hem de altın

fiyat getirilerinin daha oynak olmasını etkilediğine dair kanıt veriyor, ancak pandeminin ortalama üzerinde önemli bir etkisi yok Bitcoin'in değerleri ve altın fiyat getirilerinin yanı sıra, covid-19 tüm dünyada insanların hareketini kısıtlamış, altının madenciliği, nakliyesi ve fiziki kullanımı ve sadece dijital olarak üretilip ticareti yapılan bitcoin'den farklı olarak etkilenmiş, bu tezin sonuçları ayrıca covid-19'un altın hacimlerinin hem ortalama değerleri hem de oynaklıkları üzerinde etkisi olduğunu ancak bitcoin hacimlerinin hem ortalama değerleri hem de oynaklıkları üzerinde hiçbir etkisi olmadığını doğrular.

Anahtar Kelimeler: Altın, Covid-19, Bitcoin, Oynaklık.

ABSTRACT

THE EFFECTS OF COVID-19 PANDEMIC ON THE VOLATILITIES OF THE DYNAMICS OF BITCOIN AND GOLD

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The emergence of the health crisis, covid-19 in this advanced technological era where connections between markets, nations, and economies have grown stronger than ever before, both the physical and digital financial markets were affected by the shock of the covid-19 pandemic rapidly. The Chinese financial market experienced the first consequences of the covid-19 pandemic. The shocks in the Chinese stock markets spilled over to other financial markets like bitcoin, gold, and others in the world. This thesis focuses on the impact the covid-19 has on volatility in the dynamics of bitcoin and gold. There exist some similarities like both bitcoin and gold having online platform for trading and some differences like physical form that gold has but bitcoin doesn't. This paper argues that these similarities and differences between these financial assets play major roles in how the covid-19 crisis affected their respective markets. The research employs the GARCH model by using ARMA as the mean equation and examines the impact of the health crisis (Covid-19) on the volatilities of the price returns and volume returns of bitcoin and gold using daily data which ranges from 9/22/2014 to 3/31/2022. The empirical results of the estimation give evidence that, covid-19 impacted the volatilities of both bitcoin and gold price returns, making them more volatile. However, the pandemic has no significant impact on the mean values of bitcoin and gold price returns.

Furthermore, the covid-19 restricted the movement of people all over the world, mining, transportation and physical usage of gold were affected, unlike for bitcoin, which is produced and traded digitally only. The results of this thesis also verify that the covid-19 has effects on both the mean values and the volatilities of the gold volumes, but has no effect on both the mean values and volatilities of the bitcoin volumes.

Keywords: Covid-19, Bitcoin, Gold, Volatility.

DEDICATION

“Thanks be to Allah” “الحمد لله”

This dissertation work is firstly dedicated to my mother, Adizah Ali, who has been my source of inspiration, support, and encouragement throughout my life. I also dedicate this thesis to my father, Musah Abubakar, my uncle Yahaya Abubakar, my aunty Bintu Ali who taught me the significance of discipline, and to all my family and friends who have been there for me during my ups and downs in life.

Finally, I dedicate this thesis to all the victims of the covid-19 pandemic disease.

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Last but not least, I need to express my gratitude and deep appreciation to my first and greatest teacher who has played the most significant and major role in the person I am today, thank you my mother, Adizah Ali, for the hospitality, knowledge, encouragement, and wisdom you have supported and inspired me with throughout my life.

It's unfair to use these limited vocabularies to try and express my gratitude to the unrepayable efforts you have all put in order to help me achieve this goal. May the Almighty bless your efforts.

Mohammed Musah

ISTANBUL, 2022

TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

CHAPTER I

INTRODUCTION

In the world of technological advancement, the connections between international markets, financial systems, and nations' monetary policies are becoming stronger and stronger. This has resulted in both positive and negative drastic spillover from one economy to another, from one financial market to another, as well as from one international financial asset to another. Risks in portfolios are rising as diversification of assets in the portfolio as a strategy for minimizing risks is becoming less effective due to the integrations and spillovers between assets becoming more intense than before. Higher volatilities, fluctuations in prices, and volumes of financial assets are usually observed in times of crisis in the financial markets. These financial crises are usually fueled by uncertainties in the environment, which can cause panic, speculation, bad news, inefficiency in the macroeconomic variables, or even epidemics.

The coronavirus (covid-19), which emerged in China in December 2019 and spread to other parts of the world, was declared by the World Health Organization (WHO) as a pandemic on March 11, 2020. The Chinese financial market experienced the first consequences of the covid-19 pandemic. Due to the current technological advancement, the connections between China's main stock markets and other financial markets like the cryptocurrency and precious metals markets are tighter than before. The volatility connections between these markets developed much stronger during the covid-19 health crisis. Just like the way the covid-19 virus spread all over the world, the shocks in the Chinese stock markets spill over to the other financial markets in the world, causing financial assets like bitcoin, Gold, and others to be more volatile and riskier during the period of the pandemic (Sharma, 2020) (Corbet et al., 2020).

With the dynamic development and rising of technology from the latter part of the 20th century, much has changed in the financial aspects of the world economy, making mention of great innovations like the use of credit and debit cards, automated teller machines (ATM), Internet banking, etc., all of these great innovations in one way or the other trying to provide some sort of solution to the liquidity, supply, and circulation of money. On October 31, 2008, the long-awaited possibility of opening doors to future currencies emerged: Bitcoin. A cryptocurrency, Bitcoin, was introduced on October 31, 2008, for the first time with a computer science paper explaining how it would function. Moreover, the code was released on January 3, 2009and the first bitcoins popped up (Small, 2015). A cryptocurrency is a virtual or digital currency that uses a cryptographic system to secure legitimate transactions with a decentralized structure, which frees them from being under the control of a centralized authority but is rather based on a distributed network across a wide range of computers. This gives the opportunity of providing virtual payment between two users directly without the need for any central trusted authorities like banks and governments.

Fast, secure, cheaper, and more comfortable means of transactions across the globe are some of the pros they come with. They also have the feature of keeping the information of parties in the transaction private and anonymous enough, which makes it an easier means of payment for some illegal economic activities and black markets. Bitcoin is the first cryptocurrency and is currently the most dominant cryptocurrency market. The direction of academic economic research has turned to the cryptocurrency bitcoin, among others, especially because of its amazing blockchain technology. Bitcoin is a computer-based currency not backed by any legal currency and has no physical form. Therefore, it does not give any sort of guarantee, which makes its volatilities higher in nature than other financial instruments like Gold (Li & Wang, 2017) (Tschorsch & Scheuermann, n.d.). A whole new window for questions was raised with the emergence of bitcoin and its high volatility, which is drawing the attention of the whole world.

Historically, one of the earliest forms of money is regarded to be Gold (Baur & Glover, 2012; Bordo, 1981). Among the precious metals market, Gold has been the most dominant since history began, and it is still the most recognized trusted precious metal internationally. It has the reputation of serving as a strong asset to store value and a medium of exchange for centuries due to its excellent physical characteristics, durability, portability, divisibility, and unique standardized features (Jastram, 2009). Throughout history, Gold has been kept for being precious. This is due to its scarcity and limited supply. The free market determines gold prices, that is, the forces of demand and supply, after the end of the Bretton Woods System in 1971. Since then, the prices of Gold have become more volatile than before. Gold is also argued to be negatively correlated with financial cycles and provides shade during a financial crisis (Bouri et al., 2020). Evidence from (Sjaastad, 2008), due to the low responsiveness of gold supply to price changes, the price of Gold in the short run is mainly determined by the forces coming from demand. In the long run, both the forces of demand and supply set the price of Gold. Monetary macroeconomic instruments and political activity indicators mostly have great effects on the price of Gold.

Gold has online platforms as well as bitcoin, where both assets can be traded online worldwide. As of the beginning of June 2022, the market capitalization in the precious metals is led by Gold with a market capitalization of around 11.7 Trillion US dollars at the price of 1,850 US dollars per ounce, followed by silver and palladium with 1.2 Trillion and 345 Billion respectively. In the market of cryptocurrencies, there are more than 10,000 cryptocurrencies in the world, and the total market capitalization of all cryptocurrencies is around 1.3 trillion US dollars. The market capitalization of the leader, Bitcoin, is 567 billion, followed by Ethereum with 215 billion at prices around 30,000 and 1,800 US dollars, respectively (source: Yahoo Finance).

Bitcoin and Gold are traded online worldwide, but Gold can also be traded in a face-to-face market as it has a physical form, is mined physically, and is also used in many physical ways, whereas bitcoin has no physical form as it is digitally generated and cannot be used in any physical form.

According to research, there exist many significant similar characteristics between bitcoin and Gold. Both assets are believed to have apolitical attributes and safe haven features during a crisis and are not dependent on inflation for their price increase (Bouri et al., 2020). Due to these relevant properties bitcoin possess as Gold, it has gained attributes like "the digital gold "(Popper, 2015; Selmi et al., 2018). In some aspects, bitcoin tends to have a unique upper hand because bitcoin purely relies on a cryptographic system on computers which is independent of decisions and politics of the country's authorities. Therefore bitcoin is not affected by the general trend and financing of common assets like Gold. These common characteristics and differences between bitcoin and Gold make it reasonable and relevant to investigate the volatilities of their returns during times of stress in the world to know the role their similarities and differences played during the period where governments and authorities all over the world implemented many fiscal policies and restricted both some physical and economic movements to minimize the stress and impact of the covid-19 pandemic on both the physical and economic health of the nations (Cheng et al., 2020; Gourinchas, 2020), both the physical financial and digital financial markets were affected by the shock of the covid-19 pandemic. Hence this study investigates the impact of the covid-19 health pandemic on the volatility returns of prices and volumes of bitcoin and Gold. This paper argues that these similarities and differences between these financial assets play major roles in how the covid-19 crisis affected the dynamics of the bitcoin and gold markets.

The generalized autoregressive conditional heteroscedastic (GARCH) models have proved to be strong and consistent in modelling time series in which their volatilities vary with time. Bitcoin and Gold both have time-varying volatilities and are also strongly dependent on their past values. Therefore, this study investigates the volatilities of bitcoin prices and volumes and gold prices and volumes using the autoregressive moving average (ARMA) as the mean equation in the standard GARCH to check the impact of the covid-19 on the volatilities in both the mean and variance of the dynamics of bitcoin and Gold.

This paper is divided into five parts. The introduction is the first part, followed by the relevant past studies surrounding the dimensions of this paper. The third part describes the data and methodology employed in this study. The estimation results and empirical analysis are in the fourth chapter of this paper, and the final chapter is the conclusion.

CHAPTER II

LITERATURE REVIEW

Recently, in cryptocurrencies markets, bitcoin, and precious markets, Gold have been on top of the most popular and important economic fields driving the world's economy and resulting in many discussions and grabbing the attention of many researchers. Wide range of literature on bitcoin and Gold from different aspects such as their price dynamics, internal and external shocks to the markets, and how they perform under the shocks. After the emergence of the health crisis, covid-19, several pieces of literature have been released trying to examine the effects of this health crisis on all bitcoin and Gold dynamics.

Bitcoin is already a computer-based currency and is not backed by any legal currency and has no physical form; therefore, it does not give any sort of guarantee, which makes its volatilities higher in nature than other financial instruments like Gold (Li & Wang, 2017; Tschorsch & Scheuermann, n.d.). The pandemic disease, Covid-19, emerged in China and started to spread to other parts of the world in 2019. The Chinese financial market experienced the first consequences of the covid-19 pandemic, and the volatility connections between China's main stock markets and bitcoin developed strongly during the health crisis, the shocks in the Chinese stock markets spillover to the other financial markets in the world causing financial assets like bitcoin, Gold, and others to be more volatile and riskier during the period of the pandemic (Corbet et al., 2020; Sharma, 2020). Also, (Salisu & Ogbonna, 2021) employed an hourly dataset for cryptocurrencies from September 2019–September 2020 and argued that an increase in the volatilities of the returns of cryptocurrencies was observed after the announcement of the covid-19 pandemic compared to the periods before the declaration of the covid-19 as a pandemic.
Similarly,(Chen et al., 2020) researched the influence fear sentiments due to the pandemic have on the price dynamics of Bitcoin. They used the hourly Google search data about the covid-19 as a proxy, and their results indicate that the volatility of the Bitcoin market

intensively became worse as searches about the covid-19 increased. This led to negative price returns for Bitcoin and an increase in the trading volume of Bitcoin.

The returns of Gold became negative after the spread of covid-19 worldwide, yet it provided a safe haven during the world financial crisis caused by the health crisis covid-19. Historically, Gold has a reputation of being classified as a "safe haven" as it has been seen as a natural currency and a very strong value metal. It is also negatively correlated with financial cycles, which means it provides shade during financial crises (Bouri et al., 2020; Dutta et al., 2020). As the supply of Gold was hugely affected by the covid-19, while it could provide a safe haven, the demand increased, resulting in the rise of its prices during the period of the pandemic. Evidence from (Sjaastad, 2008) reveals that due to the low responsiveness of gold supply to price changes, the price of Gold in the short run is mainly determined by the forces coming from demand. In the long run, both the forces of demand and supply set the price of Gold. Monetary macroeconomic instruments and political activity indicators mostly have great effects on the price of Gold.

Moreover,(Wen et al., 2022) employed a daily dataset covering the period from January 2019 to June 2021 using TVP-VAR and provided results that, during the Covid-19 pandemic, Gold was able to maintain its safe haven role in the financial markets while Bitcoin rejected the safe haven role. Their results also show that the role gold played as a safe haven in the financial markets increased and became stronger when the covid-19 disease rapidly spread, but (Bouoiyour & Selmi n.d.) argued for both bitcoin and Gold where they claim the volatility of bitcoin prices became very intense due to the covid-19 pandemic; however, bitcoin can maintain its safe haven role despite the intensified volatility caused by the covid-19. Moreover, bitcoin responses to the covid-19 events are not immediate; the shocks take time before reflecting in the bitcoin markets.

However,(Chemkha et al., 2021) employed the multivariate asymmetric dynamic conditional correlation model and argued that the feature of Gold and bitcoin as hedging assets in minimizing the risk in worldwide portfolios is statistically significantly reduced due to the covid-19. Moreover, the safe-haven property of Gold has become weak, and the higher volatility of Bitcoin makes it unable to supply shelter as a safe haven during the pandemic. During the covid-19 pandemic, bitcoin prices statistically significantly became highly volatile. Moreover, the volatility correlation between the bitcoin prices and bitcoin's trading volume is positive (Liu & Lee, 2020). They employed the ARMA GARCH model with time series data set of bitcoin from January 2012 to April 2020. Their empirical results also point to a significant positive connection between news flow and condition volatility as well as a significant inverse connection between information asymmetry and the price returns of bitcoin. Moreover,(Ozturk & Cavdar, 2021) investigated the impacts of the covid-19 on the volatilities of several financial variables, including bitcoin prices and gold prices, by employing the ARMA-EGARCH model using a daily data set from September 2019 to December 2020. They provided evidence that within that short period, the covid-19 pandemic had a statistically significant impact on the bitcoin and gold prices, causing excessive fluctuations in their prices and contaminating mutual volatilities between them.

González et al. (2021) employed the NARDL model using a dataset from the early stages of the pandemic (March 2020–June 2020). Their empirical results show that the correlation between cryptocurrencies and Gold increased, and more of the cryptocurrencies had their returns cointegrated with the returns of Gold. They also provided evidence that during the covid-19, cryptocurrencies formed both short- and long-term asymmetric responses to the returns of Gold, especially to the negative changes in the returns of Gold.

CHAPTER III

METHODOLOGY AND DATA COLLECTION

The source of the data and the econometric methodologies employed in this study are detailed in this section of this paper.

3.1. Data Sources

The data sample used in the study is presented in the table below as well as the sources, the period and the abbreviations used to represent the study's various variables.

Table 3.1. Variables and Data Sources

Variable(s)	Representations	Data Frequency	Period	Data Source
Bitcoin Price	BP	Daily	9/22/2014 - 3/31/2022	Yahoo Finance
Bitcoin Volume	BV	Daily	9/22/2014 - 3/31/2022	Yahoo Finance
Gold Price	GP	Daily	9/22/2014 - 3/31/2022	Yahoo Finance
Gold Volume	GV	Daily	9/22/2014 - 3/31/2022	Yahoo Finance

The convention process of the bitcoin prices, gold prices, bitcoin volume, and the gold volume into returns series which is used in the study, are summarized below.

3.1.1. Returns of The Series

For the estimations in this paper, the returns of the series are employed for the estimations. Much remarkable financial research makes use of the series' returns as it gives investors easy and complete information about the risks and opportunities of the assets. For statistical purposes, the returns are simpler and more effective to employ than the actual prices of the assets due to their unique statistical features (Campbell et al., 1998; Tsay, 2005).

The mathematical expression of the returns of series is expressed as;

$$r_t = \ln(1 + R_t) = ln\left({}^{X_t}/_{X_{t-1}}\right) = x_t - x_{t-1}$$

$$p_t = \ln(X_t)$$

$R_t = \sum_{i=1}^{N} w_i R_{it}$, R_{it}= Simple Return of series i

$$r_t \approx \sum_{i=1}^{N} w_i r_{it}$$

Where;

r = the return at time "t"

x = the series value at time t.

3.2. Methods

This paper employs various econometric methodologies, starting from checking the stationarity of the time series variables in the study and examines the impact the health crisis Covid-19 has on the volatilities of the price returns and volumes returns of bitcoin and Gold by employing the GARCH model, using ARMA as the mean equation.

3.2.1. Unit Root Test

The unit root test is a standard method for testing stationarity in a time series, determining whether a variable follows a random walk or not. Using a set of data for estimations and analyses that is not stationary may give misleading and spurious results, as data sets having unit root turns to be biased, which, when used, may lead to a biased result. It is then necessary to check for the stationarity of a data set before using it in estimations.

In testing for the stationarity of the variables used in the study, three different unit root testing methods were employed, the Dickey-Fuller GLS (DF GLS), the Elliott-Rothenberg-Stock Point-Optimal (ELRS Optimal), and the Kwiatkowski-Philips-Schmidt-Shin (KPSS).

Dicky-Fuller GLS (DF GLS)

The DF-GLS is a modified and improved Augmented Dicky–Fuller (ADF) method for testing unit roots in a time series by transforming the time series using the generalized least squares (GLS) before performing the test. The DF-GLS was proposed by Elliot, Rothenberg, and Stock (ERS) in their 1996 Econometrica article. The DF-GLS has significantly improved power when an unknown mean or trend is present in the series compared to the previous versions of the ADF.

Firstly, the generalized least squares (GLS) detrending procedure is fitted.

$$y_t^d \equiv y_t - x_t'\hat{0}(\bar{a})$$

Next is estimating standard ADF test regression by using the GLS detrended y_t^d for the initial y_t :

$$\Delta y_t^d = a y_{t-1}^d + \beta_1 \Delta y_t^d + \cdots + \beta_p \Delta y_{t-p}^d + v_t$$

The trend is included in the DF-GLS test by default; therefore, the test can run under two specifications, with trend and intercept or with the trend only. The null hypothesis of the

DF-GLS is similar to the ADF; thus, the series is non-stationary. The null hypothesis of non-stationary is rejected when the T-statistic is less than the critical values of the DF-GLS test.

Elliott-Rothenberg-Stock Point-Optimal (ERS Optimal)

Elliot, Rothenberg & Stock (1996) proposed a point optimal "P-test" which considers the serial correlation which may be present in the error term in order to improve the power of the unit root test.

They can be mathematically expressed as follows:

Let $SSR(a) = \sum \hat{\eta}_t^2(a)$ be the sum of squared residuals

where $\hat{\eta}_t(a) = d\left(y_t|a\right) - d\left(x_t|a\right)'\hat{o}(a)$

The null hypothesis states that $a = 1$, alternative hypothesis $a = \bar{a}$, the equation is then defined as :

$$P_t = \left(SSR(\bar{a}) - \bar{a}SSR(1)\right)/f_0$$

Where f_0 , is a residual estimator at frequency zero. The null hypothesis of the ERS point optimal is non-stationary, as opposed to the alternative of being stationary for the observable time series. The null hypothesis of non-stationary is rejected when the P-statistic is less than the critical values when using the ERS optimal tests.

Kwiatkowski-Philips-Schmidt-Shin (KPSS)

The KPSS tests are used on the null hypothesis that the time series is stationary against the alternative of unit root, which is opposite to most of the various unit root tests in the literature, such as Dickey-Fuller, DF-GLS, and Phillips-Perron tests. Therefore, the KPSS tests are commonly used as complementary tests to verify the results of the other unit root tests.

They can be mathematically expressed as follows:

$$y_t = d_t + r_t + \varepsilon_t,$$

$$r_t = r_{t-1} + u_t,$$

The $d_t = \sum_{i=0}^{p} \delta_i t^i$,

$p = 0{,}1,$ the deterministic components of the equations (thus; trend and constant),

ε_t are iid $\mathrm{N}(0,\ \sigma_\varepsilon^2), r_t$ That is a random walk with the variance σ_u^2 and u_t are iid $N(0, \sigma_u^2)$.

The null hypothesis is that the random walk is with a variance of zero; $H_0: \sigma_u^2 = 0,\ r_t$ is constant. The alternative hypothesis is ; $H_1: \sigma_u^2 > 0$.

Therefore, the test statistic of KPSS is written as:

$$LM = \sum_{t=1}^{T} \frac{se_t^2}{\widehat{\sigma_t^2}},$$

Where $se_t \sum_{t=1}^{t} \widehat{\varepsilon_t}$, $t = 1, 2, \ldots, T$ and $\widehat{\sigma_t^2}$ is the variance estimate of the residual process ε_t from the initial equation.

The KPSS uses a one-sided LM statistic. Therefore, if the LM test statistic is greater than the critical value, the null hypothesis of stationary is rejected, meaning the time series variable under observation is non-stationary.

3.2.2. Specification of the Conditional Mean Equation

The ARMA model is used as the mean equation of the GARCH model used in this study. The ARMA is a commonly used statistical method in models for analysis to get the predictions for time series as the ARMA uses the lag order process of the time series, taking into account the past shocks and values of the time series in the prediction of the future values.

The ARMA combines the interactions of the Autoregressive (AR) lag orders and the Time series Moving Average (MA).

The Autoregressive (AR) lags order can be mathematically represented as:

ε_t : AR(p)

$$r_t = \sum_{i=1}^{p} \delta_i r_{t-i} + \varepsilon_t \ ,$$

$$\begin{Bmatrix} \epsilon_t \sim (WN) \\ \epsilon_t \sim IID(0, \sigma^2) \end{Bmatrix}$$

Whereas the Moving Average (MA) lags order can be mathematically represented as:

ε_t: MA(q)

$$r_t = \sum_{j=1}^{q} \varphi_j \varepsilon_{t-j} + \varepsilon_t \ ,$$

The Moving Average MA(q) is a process in stationary form whereas ε_t is a mean zero with variance σ^2 sole distribution. Therefore ARMA (p, q) is illustrated as follows:

$$r_t = \mu + \sum_{i=1}^{p} \delta_i r_{t-i} + \sum_{j=1}^{q} \varphi_j \varepsilon_{t-j} + \varepsilon_t$$

After the proportionate Autoregressive (AR) and the Moving Average (MA) terms of the tentative ARMA models were tested, the information criteria used in the selection of the best fits in this study are Akaike Information Criteria (AIC) and Bayesian Information Criteria (BIC).

AIC $= -2\ln(L) + 2k$

BIC$= -2\ln(L) + k\ln(T)$

L = the value of the maximized likelihood function

k = $= p + q + 1$, the constant plus the other parameters.

The model with the lower information criteria value is the better model, meaning the model with lower errors.

3.2.3. ARCH Effects

After selecting the appropriate ARMA models for the series in the study, the next step is testing for the existence of serial correlation in the volatility of the series, the ARCH effect, before using the ARMA model as the mean equation for the GARCH models.

Omitting the ARCH effects may result in huge losses in asymptotic efficiency (Engle, 1982a) and may lead to excess rejection of the autocorrelation (AC) of normal standardized tests in the conditional mean (see Taylor, 1984 and Diebold, 1987).

The null hypothesis of the ARCH-LM is the absence of the ARCH effect in the auxiliary regression, which is estimated; therefore, the alternative hypothesis is the ARCH effect in the residuals obtained. The regression is mathematically computed as follows:

$$\epsilon_t^2 = \beta_0 + \left(\sum_{i=1}^{q} \beta_1 \epsilon_{t-1}^2\right) + v_t$$

The squared residuals. "ϵ_t^2" with an intercept and the total lag of squared residuals of the order q. The F-statistics, thus the significance of the lagged squared residuals of the neglected variable tests and the(Engle, 1982) 's maximum likelihood statistic*R-squared statistics are the outputs from the regression. The ARCH-LM test can be mathematically also represented as:

$$ARCH_{LM}(q) = TR^2$$

Where the total observation is denoted by T and R^2 is the squared residuals.

The ARCH-LM test is used in the post-estimation tests to check if the estimated model was able to capture the ARCH effects or not, where rejecting the null hypothesis means that there are still ARCH effects present, and the null hypothesis not rejected means there are not any ARCH effects left in the time series.

3.2.4. GARCH

After the autoregressive moving average model (ARMA) is assumed to have ARCH effects, the model is now computed into a generalized autoregressive conditional heteroscedasticity (GARCH) model.

In this situation, the model (GARCH (p,q)) is expressed as follows;
The order of GARCH terms σ^2 , is represented by p
The order of ARCH terms $\in^2$, is represented by q.
The GARCH (p, q) model is illustrated as follows;

$$yt = x_t{}'b + \in_t$$

$$\in_t/\varphi_{t-1} \sim N(0, \sigma_t^2$$

$$\sigma_t^2 = w_0 + \sum_{i=1}^{q} \alpha_i \epsilon_{t-i}^2 + \sum_{j=1}^{p} \beta_i \sigma_{t-j}^2$$

The specification of the GARCH(p,q) model generally follows these three steps.

Firstly, estimating the best-fitting autoregressive(ARMA) model, then the autocorrelations of the error term are calculated, and the last step is testing for significance.

CHAPTER IV

EMPIRICAL RESULTS

4.1. Descriptive Statistics

The summary statistics of the Bitcoin prices, bitcoin volumes, gold prices, and gold volumes are presented in the table below. The minimum bitcoin price is $197, which is less than the minimum of gold prices, but the maximum bitcoin price is $6,456, which is greater than the maximum of gold prices within the same time frame, and also the standard deviation of bitcoin prices is $16491, which is also greater than the standard deviation of gold prices of $263, which shows how volatile the bitcoin prices have been compared to the gold prices within the same period. As the skewness of a normally distributed series is zero, and the kurtosis of a standard normal distribution is 3, it is obvious that all the series are not normally distributed, with gold volume having the highest skewness followed by bitcoin volume, bitcoin prices, and gold prices.

Table 4.1. Descriptive Statistics for the Returns of Bitcoin and Gold Prices and Volumes

STATISTIC	Bitcoin Prices	Gold Prices	Bitcoin Volume	Gold Volume
Mean	11833.32	1421.230	1.55E+10	5709.960
Median	6415.078	1297.400	5.40E+09	153.0000
Maximum	67456.20	2051.500	3.51E+11	386334.0
Minimum	197.7020	1055.400	7845880.	1.000000
Std. Dev.	16491.01	263.7656	2.10E+10	31471.01
Skewness	1.727448	0.737084	3.409424	7.034618

Table 4.1. (cont.)

Kurtosis	4.720196	2.043380	38.86076	56.50422
Jarque-Bera	1165.564	241.6588	104267.4	239495.4
Probability	0.000000	0.000000	0.000000	0.000000
Sum	22222977	2669070.	2.91E+13	10723304
Sum Sq. Dev.	5.10E+11	1.31E+08	8.29E+23	1.86E+12
Observations	1878	1878	1878	1878

4.2. Graphical Representation of The Series

The original series of daily prices and volumes of bitcoin and Gold and the returns are graphically shown in the graphs below, covering the period from September 22, 2014, to March 31, 2022. The natural log of Bitcoin's daily prices and the natural log of Gold's daily prices are respectively represented by Figure 4.1 and Figure 4.2. The daily price returns are represented by Figure 4.5. for Bitcoin and, Figure 4.6. for Gold, Figure 4.3. visualizes the natural log of bitcoin daily trading volume, Figure 4.4. for the natural log of gold daily trading volume, the daily returns of the volumes are shown in Figure 4.7. for Bitcoin and Figure 4.8. for Gold.

In April 2021, the bitcoin market experienced a rapid bull run (price rise) which took the bitcoin price up to $64,000, then down to $30,000 in June 2021, then a drastic rise again to $67,000 in October 2021, followed by another decline in price in January 2022 and since then the prices have been stable at around $40,000. Before these recent high spikes in prices, the highest bull run was in December 2017, when the bitcoin prices rose to $19,000. During the recent rise in the bitcoin prices, gold prices faced a slight bear run (fall in prices) from $2,000 in October 2020 to $1,700 and were stable around $1,750 in April 2021. A similar scenario was also observed during the 2017 rise in the price of bitcoin, where gold prices fell from $1300 to $1240 over a period of 4 months before bitcoin hit $19,000. In both scenarios, the Gold prices experienced drastic bull runs immediately after bitcoin hit the peaks. Now both the daily bitcoin and gold prices are on an upward trend; however, the volatility of the bitcoin's daily prices is too high compared to the volatility of the daily gold prices.

The daily trading volume of Gold has been almost the same throughout the period visualized in Figure 4.4. On the other hand, bitcoin's daily trading volume was very low during the early stages. As can be seen in Figure 4.3., the bitcoin trading volume began to rise after the 2017 drastic spikes in its prices, and since then, it has been in trends with high volatility, especially during bull runs. In the recent bull run of the bitcoin prices, its trading volume spiked more than 300 percent and immediately fell back within a day. Since then, it has been a downward trend with several upward spikes in the daily trading volume.

The daily price returns of bitcoin and Gold are respectively visualized in Figure 4.1. and Figure 4.2. Both returns show volatility clustering around zero, but the returns of bitcoin appear to have higher volatility with a leptokurtic nature than the returns of Gold, which appear to have very intense low volatility around zero as compared to that of bitcoin.

The daily trading volume returns of bitcoin and Gold, respectively graphically shown in Figure 4.7. and Figure 4.8. show the vice versa relations that the price returns have. The bitcoin volume returns show clustering around the constant with lower volatility compared to the volume returns of the gold series, where higher volatility around the content zero is visualized.

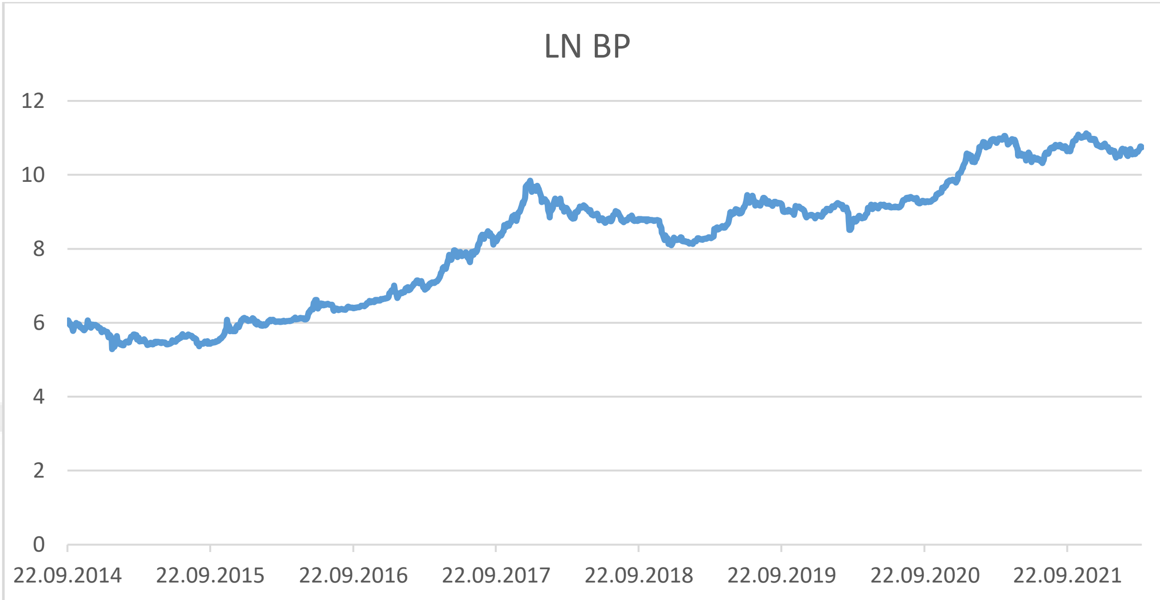

Figure 4.1. Daily Prices of Bitcoin (logged)

Figure 4.2. Daily Prices of Gold (logged)

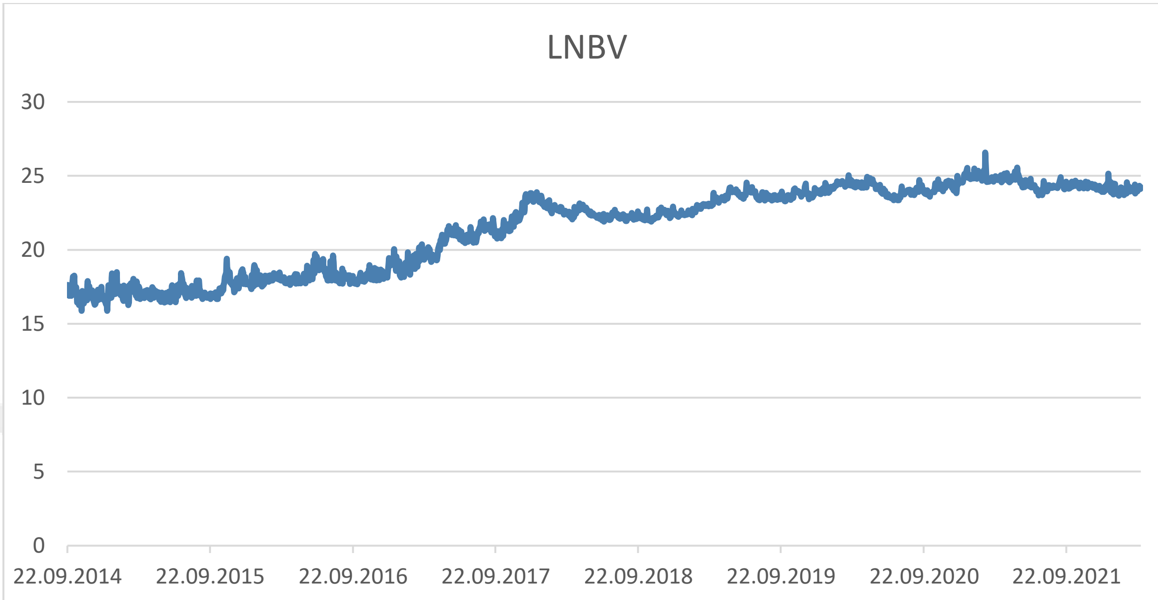

Figure 4.3. Daily Trading Volume of Bitcoin (logged)

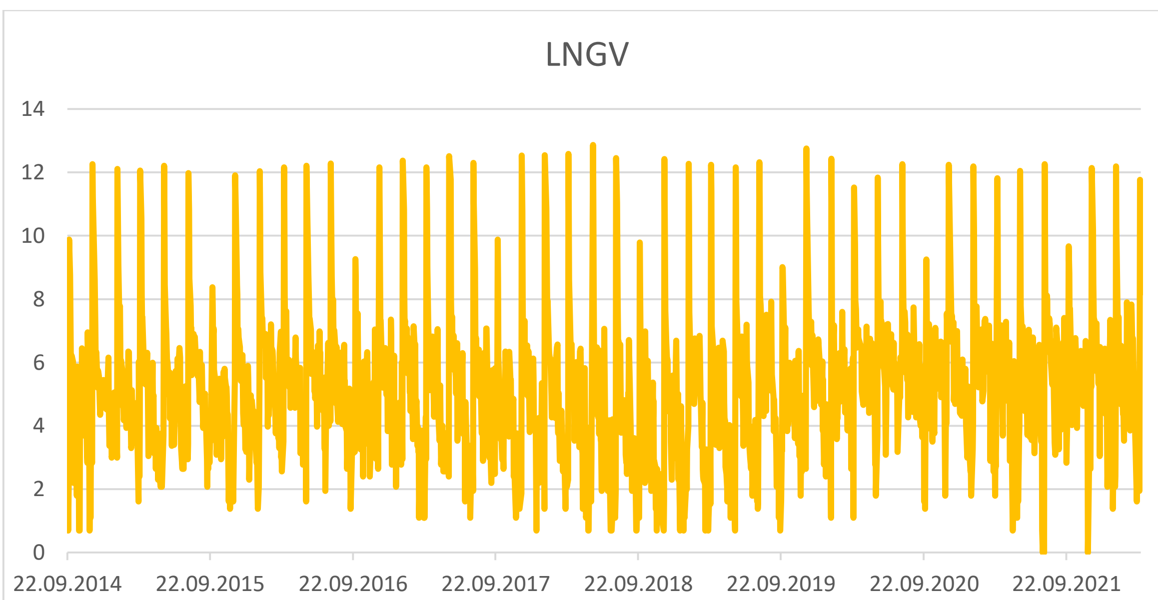

Figure 4.4. Daily Trading Volume of Gold (logged)

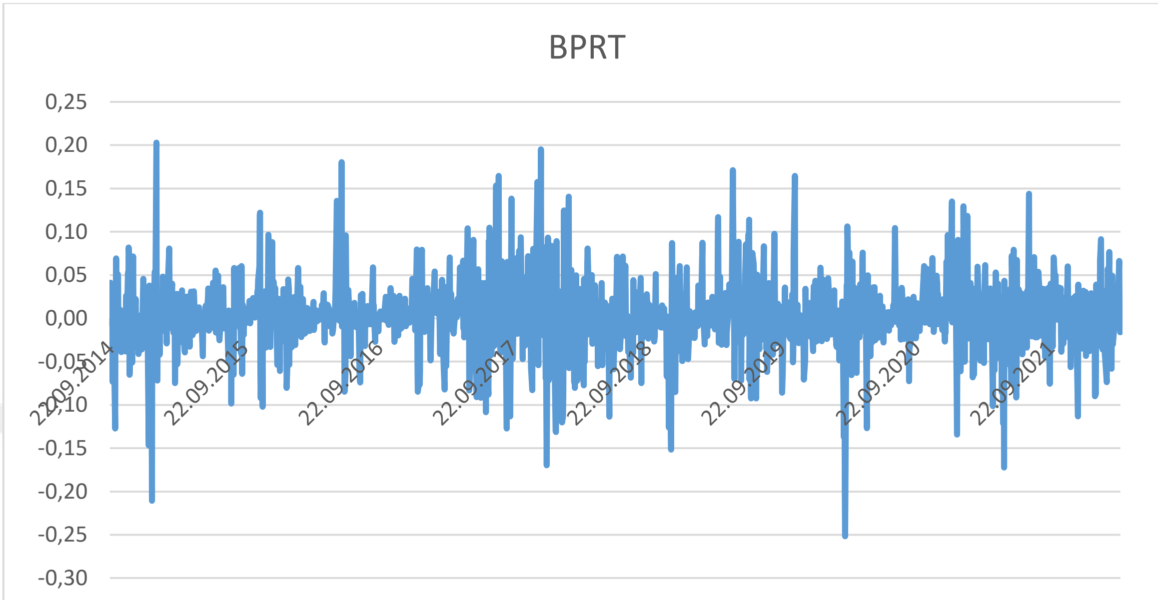

Figure 4.5.. Daily Price Returns of Bitcoin

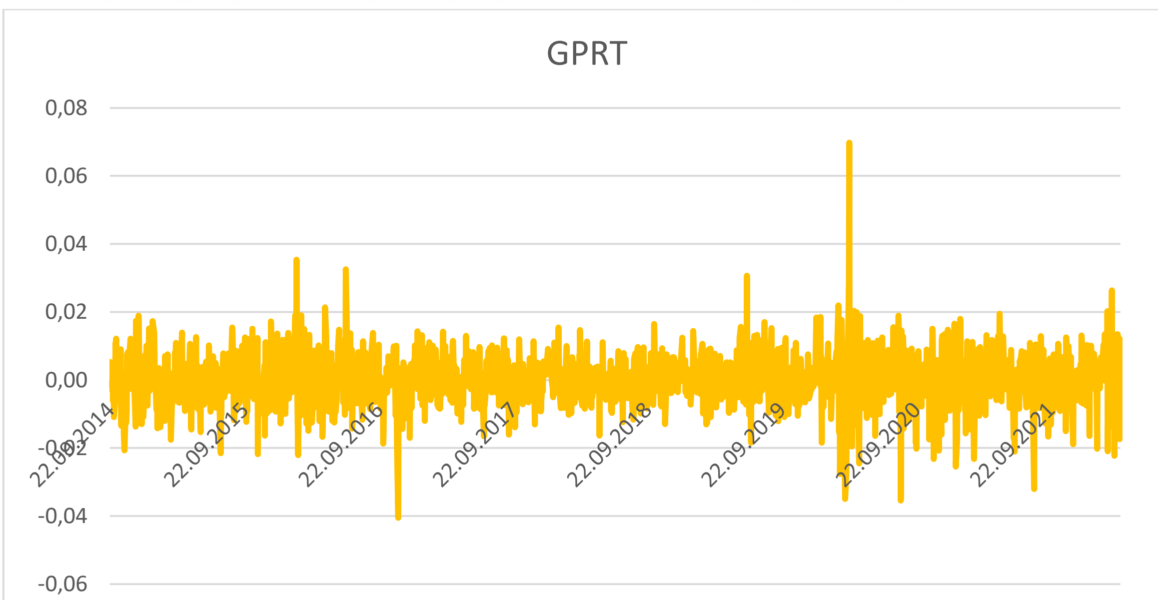

Figure 4.6. Daily Price Returns of Gold

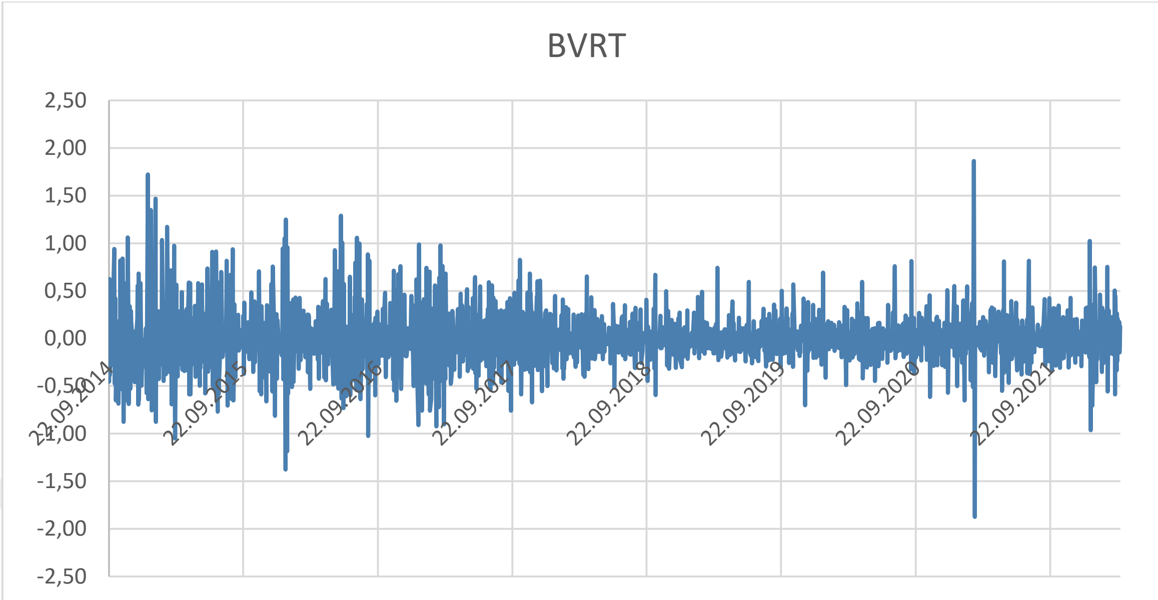

Figure 4.7. Daily Volume Returns of Bitcoin

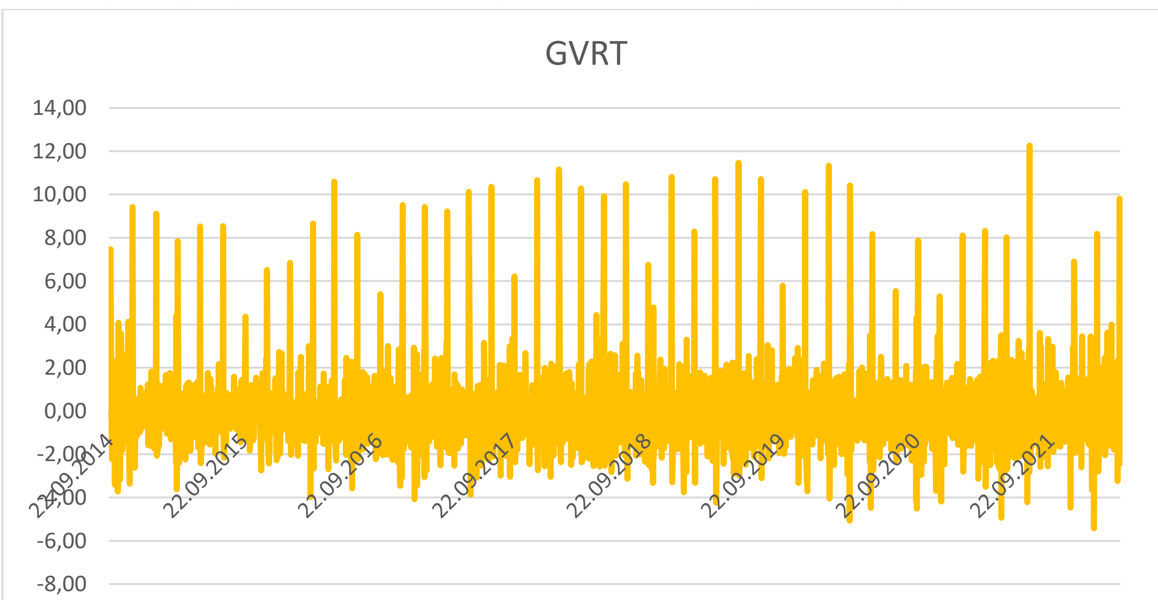

Figure 4.8. Daily Volume Returns of Gold

4.3. Unit Root Test Results

Using the three different unit root tests explained above, the variables' stationarity was tested firstly at levels and then after their first differenced under two specifications; 1. With intercept only, 2. With both intercept and trend components present.

Below is the summary of the unit root test results of the bitcoin price, gold price, bitcoin volume, and gold volume.

Table 4.2. Unit Root Tests Results

Tests	Variables	At Level		First Difference		Conclusion
		Constant	Trend	Constant	Trend	
Dicky-Fuller GLS (DF-GLS)	LNBP	1.431	-1.704	-5.688***	-10.187***	I(1)
	LNGP	0.322	-1.767	-8.053***	-30.880***	I(1)
	LNBV	0.349	-2.629*	-1.549	-3.304**	I(1)
	LNGV	-5.329***	-11.364***	===	===	I(0)
Elliott-Rothenberg-Stock Point-Optimal (ERS	LNBP	115.803	15.785	0.063***	0.129***	I(1)
	LNGP	25.585	13.861	0.034***	0.103***	I(1)
	LNBV	56.592	6.727*	0.024***	0.035***	I(1)
	LNGV	0.171***	0.221***	===	===	I(0)
Kwiatkowski-Philips-Schmidt-Shin (KPSS)	LNBP	5.109***	0.398***	0.094	0.094	I(1)
	LNGP	4.670***	0.757***	0.113	0.036	I(1)
	LNBV	5.252***	0.868***	0.095	0.046	I(1)
	LNGV	0.563**	0.355***	0.053	0.052	I(1)

The DF GLS and ELRS optimal unit root tests results for the bitcoin price time series and gold price time series show that the test statistics with constant only and with both constant and trend are statistically insignificant at level but statistically significant at the first difference. That is, the null hypothesis of both the DF GLS test and ELRS optimal unit root tests, which is non-stationarity, cannot be rejected at a level and is rejected after the first difference of the time series at a one percent significant level. These results are confirmed by the KPSS unit root test, which has its null hypothesis as stationarity. The test statistics of the bitcoin and gold prices, while with constant and with both constant and trend, are statistically significant at level but statistically insignificant at the first difference. In other words, they are not stationary at a level but stationary at the first difference.

The Bitcoin volume time series proved non-stationary in all the three-unit root tests at the level with only an intercept. With both intercept and trend, the bitcoin volume time series tends to be stationary at the level for DF GLS and ELRS optimal unit root tests but non-stationary for the KPSS unit root test. The bitcoin volume time series becomes stationary for all the three-unit root tests in use with only intercept and with both intercept and trend components present.

The gold volume time series is stationary at the level for DF GLS, and ELRS optimal but not for KPSS unit root tests with the presence of only intercept and with both intercept and trend components present.

4.4. Identifying the Appropriate Conditional Mean Equation

To specify the conditional mean equations for the Garch models used in this thesis, the correlogram of the bitcoin price returns, gold price returns, bitcoin volume returns, and the log of gold volume were used in studying the autocorrelation and the partial correlation patterns that each of the variables listed above exhibits. Moreover, the results of the significant tails of the Autoregressive(AR) and Moving Average(MA) were identified as shown in the table below in the column of the Tentative ARMA models. The process was carried on by using the auto ARMA forecasting method in the EVIEWS with seven lags (as the data series are daily) for both the AR and the MA components. This is to ensure and verify the observations from the correlograms of the variables. The Bayesian Information Criteria (BIC) is used in the selections of the appropriate ARMA models instead of the Akaike Information Criteria (AIC) to avoid over-parameterized models (Ayele et al., 2017).

The heteroscedasticity in the data is then checked by employing the ARCH-LM tests proposed by (Engle, 1982) to check the presence of ARCH effects in the appropriate selected ARMA models. Both the bitcoin and gold price returns follow an AR(1) MA(0) movement, and the bitcoin volume returns follow an AR(1) MA(1) movement, while the movement of the log of gold volumes is AR(5) MA(2). The presence of ARCH effects is checked in two ways: one without the covid-19 component and the other with the covid-19 component. The ARCH effects are significantly found in both scenarios in all the appropriate models selected for all four variables. The table below summarizes the specification of the conditional mean equation.

Table 4.3. Model Selection and ARCH-LM Test

	Tentative ARMA Models		Appropriate ARMA		ARCH EFFECT	
Variables	AR	MA	AR	MA	Without CVD-19	With CVD-19
BPRT	1	1	1	0	82.672***	81.788***
GPRT	1,2	1,5	1	0	46.568***	45.374***
BVRT	1,2,3,4,5	1,2	1	1	112.342***	111.265***
LNGV	1,2,3,4,5,6	1,2,3	5	2	352.460***	356.337***

4.5. GARCH Results

In the estimation of the effects the health crisis (covid-19) has on the volatility of the returns of the time series under study, we employed the GARCH model with an ARMA equation as the mean equation. Both the bitcoin price returns and the gold price returns mean equations are specified as an AR(1) MA(0) equation. The bitcoin volume returns and log of gold volume mean equations are specified as AR(1) MA(1) and AR(5) MA(2) equations, respectively.

For each time series under study, four different equation specifications are used;
Equation 1 is complete without the covid-19 dummy variable component.
Equation 2 has the covid-19 dummy variable present in only the mean equations.
Equation 3 has the covid-19 dummy variable present in only the variance equations.
Equation 4 has the covid-19 dummy variable present in both the mean and the variance equations.

The results of the estimations are summarized in the tables below.

Table 4.4. Results of Standard GARCH (p,q) for BPRT , GPRT, BVRT and LNGV Absence of Covid-19 Variables

Equations	Parameters	Model 1			
		BPRT	GPRT	BVRT	LNGV
Mean Equation	Constant	0.002658	0.000225	0.004929**	5.315845***
	AR	0.130925***	0.171537***	0.303334***	0.055374***
	MA	---	---	-0.73801***	0.211105***
	Covid-19	---	---	---	---

Table 4.4. (cont.)

Variance Equation	Constant	0.000974***	3.80E-05**	0.020569***	0.632956***
	RESID(-1)^2	0.150000***	0.150000***	0.112026***	0.612145***
	GARCH(-1)	0.599733***	0.599973***	0.562026***	0.362774***
	Covid-19				

Table 4.5. Results of Standard GARCH (p,q) for BPRT , GPRT, BVRT and LNGV, Presence of Covid-19 Variables In Mean Equation Only

Equations	Parameters	Model 2			
		BPRT	GPRT	BVRT	LNGV
Mean Equation	Constant	0.00247	0.000178	0.005031	5.181236***
	AR	0.263721***	0.229936***	0.308243***	0.049297***
	MA	---	---	-0.742476***	0.203284***
	Covid-19	0.001051	0.000219	-0.004413	0.496084***
Variance Equation	Constant	0.000536***	3.80E-05**	0.058308**	0.641575***
	RESID(-1)^2	0.149563***	0.150000***	0.149770**	0.624228***
	GARCH(-1)	0.599563***	0.600000***	0.599770***	0.353432***
	Covid-19				

Table 4.6. Results of Standard GARCH (p,q) for BPRT , GPRT, BVRT and LNGV Presence of Covid-19 Variables In Variance Equation Only

Equations	Parameters	Model 3			
		BPRT	GPRT	BVRT	LNGV
Mean Equation	Constant	0.002297**	0.000179	0.005817**	5.314962***
	AR	0.279062***	0.226758***	0.280067***	0.053345***
	MA	---	---	-0.714595***	0.207349***
	Covid-19	---	---	---	---
Variance Equation	Constant	6.56E-05***	4.04E-06***	0.003074***	0.532640***
	RESID(-1)^2	0.135588***	0.093283***	0.131840***	0.648463***
	GARCH(-1)	0.822438***	0.824047***	0.828614***	0.345744***
	Covid-19	1.27E-05**	1.77E-06**	0.000138	0.340442***

Table 4.7. Results of Standard GARCH (p,q) for BPRT , GPRT, BVRT and LNGV, Presence of Covid-19 Variables In Both Mean Equation And Variance Equation

Equations	Parameters	Model 4			
		BPRT	GPRT	BVRT	LNGV
Mean Equation	Constant	0.0019	0.000161	0.007197***	5.200896***
	AR	0.278688***	0.226673***	0.281492***	0.048596***
	MA	---	---	-0.716103***	0.200781***
	Covid-19	0.001335	9.34E-05	-0.004499	0.468045***
Variance Equation	Constant	6.54E-05***	4.05E-06***	0.003074***	0.545716***
	RESID(-1)^2	0.135334***	0.093428***	0.132708***	0.652663***
	GARCH(-1)	0.822827***	0.823651***	0.827676***	0.344528***
	Covid-19	1.27E-05**	1.78E-06**	0.000178	0.275265***

4.5.1. Discussion of the Results of the Price Returns

The empirical results of the equation without the covid-19 component show that the effects of the past value in the prediction of the present value of the returns of gold prices are higher than those of bitcoin returns. The variance in the present value of bitcoin returns constitutes a 0.000974 constant together with a 0.599 (GARCH term) effect from the past variation and a 0.15 component which depends on the past unforeseen errors (ARCH term). This proves to be greater than the gold variance equation, which consists of a 3.80E-05 constant, 0.599 (GARCH term) effects from the past variation, and a 0.15 (ARCH term) component which depends on the past errors. This evidence proves that bitcoin price returns are more volatile than the returns of gold prices. In other words, bitcoin prices are more volatile than gold prices.

The estimation results with covid-19 in the mean equation only show that the covid-19 component is not significant, and the volatility of the bitcoin price returns and gold price returns exhibit similar movement as in the first equation where the covid-19 component is not included in the equation at all.

In equation three, where the covid-19 component is present in only the variance equation, results show that the effects of the covid-19 on the variation of the returns of both bitcoin and gold prices are statistically significant even though the effects are low with 1.27E-05 for bitcoin price returns and 1.77E-05 for gold price returns. However, the presence of the covid-19 dummy variable in the variance equation reduces the ARCH term(the prediction from past errors) from 0.15 (from equation 1 results) to 0.135 for bitcoin price returns and from 0.15 (from equation 1 results) to 0.093 for gold price returns, and it is being captured in the effects coming from the past variation on the present price returns making the increasing the GARCH terms from 0.599 (from equation 1 results) to 0.822 for bitcoin price returns and 0.599 (from equation 1 results) to 0.824 for gold price returns. This clearly shows that the effects of covid-19 on the volatility of bitcoin and gold prices are dependent on the covid-19 component in the variance equation. The effects of the past errors were greater but reduced when the component of the covid-19 was present.

With the covid-19 component present in both the mean equation and the variance equation, which is just literally the combination of the second and third equations, evidence shows that covid-19 has no significant effects on the mean values of returns of both bitcoin and gold prices but has significant effects on the price return variations.

4.5.2. Discussion of the Results of The Bitcoin Volume Returns And Log of Gold Volumes

The empirical results of the equation without the covid-19 component show that the mean equation of both the bitcoin volume returns and the log of gold volumes consists of statistically significant constants, autoregressive components, and moving average components. In the variance equation, the effects of the past variation (GARCH term) on the present variation of bitcoin volume returns is greater than that of the golds; however, the effects coming from the past errors (which are unexplained) from the log of the gold volumes is greater than that of the bitcoins volumes.

With covid-19 present in only the mean equation, the results show that covid-19 has no statistically significant role in the determination of the returns of the bitcoin volume but covid 19 has a statistically significant impact n the determination of the mean values of the log of gold volumes.

Evidence from the results of the Garch model in the third equation where covid-19 is present in only the variance equation testifies that covid-19, with the estimation value of 0.340442, proves to be statistically significant for the gold volumes but statistically insignificant for the determination of the variation of the bitcoin volume returns with the estimation value of 0.000138. In other words, covid-19 greatly affects the volatility of gold volumes but does not have any statistically proven effect on the volatility of bitcoin volumes.

With the covid-19 component present in both the mean equation and the variance equation, which is just literally the combination of the second and third equations, evidence shows that covid-19 has no significant effects on the mean values of returns of bitcoin volumes but has statistically significant effects on the gold volume mean values and volatility.

4.6. Post Estimation Tests

Table 4.8. ARCH-LM Test

		ARCH-LM TEST			
		Equation 1	Equation 2	Equation 3	Equation 4
Bprt	F-Statistics	0.146555	0.148577	0.153154	0.15501
		(0.9944)	(0.9941)	(0.9936)	(0.9933)
	Chi-Squared	1.029727	1.043927	1.076066	1.089101
		(0.9943)	(0.9941)	(0.9935)	(0.9933)
Gprt	F-Statistics	1.672959	1.658533	1.325089	1.318341
		(0.1112)	(0.1149)	(0.2342)	(0.2374)
	Chi-Squared	11.68752	11.58736	9.269301	9.222329
		(0.1113)	(0.115)	(0.2339)	(0.2371)
Bvrt	F-Statistics	0.564219	0.551386	0.564398	0.55141
		(0.7854)	(0.7957)	(0.7853)	(0.7956)
	Chi-Squared	3.958103	3.868268	3.959362	3.868435
		(0.7846)	(0.7948)	(0.7844)	(0.7948)
Lngv	F-Statistics	1.601016	1.592002	1.709968	1.686444
		(0.1306)	(0.1332)	(0.1023)	(0.1079)
	Chi-Squared	11.18788	11.12527	11.94437	11.78108
		(0.1306)	(0.1332)	(0.1023)	(0.108)

After estimating the fitted standard GARCH models using ARMA as the mean equations, we proceed by conducting the necessary post-estimation tests to validate the models we employed.

We test the validity of the models by conducting the ARCH-LM test and the correlogram test after the GARCH models' estimation using the squared residuals from the estimation.

In the pre-estimation of the fitted models, we checked the ARCH effects in the residuals and found the presence of an ARCH effect, that is, serial correlation in the squared residuals. After estimating the fitted GARCH models, four different equations for each variable, we conducted The ARCH-LM tests in the post-estimation to check if the serial correlations in the squared residuals still exist or not. The null hypothesis (Ho: Absence of ARCH effect) of the ARCH-LM in the post-estimation cannot be rejected as the F-statistics, and the Chi-squared (X2) is statistically insignificant for all four different equations of the four variables.

Similarly, the correlogram tests in the pre-estimation showed statistically significant autocorrelations in all four variables. In contrast, the results in the post-estimation correlogram test show no significant autocorrelations in the squared residuals of the fitted models anymore.

CHAPTER V

CONCLUSION

Since the emergence of bitcoin into the global financial markets, much research has been done to check the relationships between the blockchain of bitcoin and the already-known precious metal, Gold. While investors are deciding on which of them (bitcoin and Gold) to dive into and when to invest, knowledge of the similarities and differences between them and the role they play in certain conditions is necessary.

The Covid-19 pandemic, although a health crisis in this technologically advanced era, where all sectors of the world economy are more tightly integrated than ever before, caused several deaths of people and restricted the movements of humans. Both the physical and digital financial markets were affected by the shock of the covid-19 pandemic.

This thesis looks closely at the effects covid-19 has on the volatilities of the dynamics of Gold and bitcoin. Bitcoin is already very volatile in nature as it is a pure computer-based currency with no guarantee because it is not backed by any legal currency or physical assets, unlike Gold (Li & Wang, 2017; Tschorsch & Scheuermann, n.d.). Historically, Gold has had a good reputation for being classified as a safe asset during a financial crisis as it has been seen as a natural currency and a very strong value-storage precious metal. It is also argued to be negatively correlated with financial cycles, which provides shade during a financial crisis (Bouri et al., 2020). Evidence from (Sjaastad, 2008), due to the low responsiveness of gold supply to price changes, the price of Gold in the short run is mainly determined by the forces coming from demand. In the long run, both the forces of demand and supply set the price of Gold. Monetary macroeconomic instruments and political activity indicators mostly have great effects on the price of Gold.

This research uses daily data of bitcoin prices and volumes, gold prices and volumes from 9/22/2014 to 3/31/2022, and a dummy variable to represent covid-19 effective from March 11, 2020, to 3/31/2022. This paper employs the GARCH model by using ARMA as the mean equation in checking the impact the health crisis of Covid-19 has on the volatility of both the prices and volumes of bitcoin and Gold. Both bitcoin and Gold are traded on online platforms. Gold has a physical form as it is mined and used in many physical ways, whereas bitcoin has no physical form as it is digitally generated and cannot be used in any physical form. These similarities and differences help in understanding the findings of this paper.

The results from the estimated GARCH models show that during the period of covid-19, which is not a crisis coming from the financial sector of the world nor a cyber-attack into the financial markets, only the price volatilities of bitcoin and Gold increased, but no significant impact on their mean values was recorded. This makes much sense as all the functions of both bitcoin, and the digital aspect of Gold could be fully realized during the covid-19 pandemic. However, only the variation in their prices increased as people were in times of distress but not in haste to liquidate their assets. Covid-19 restricted the movement of people all over the world, and mining, transporting, and physical usage of Gold was affected. The empirical results of this thesis also testify that covid-19 affects both the mean values and the volatilities of the gold volumes but has no effect on both the mean values and volatilities of the bitcoin volumes.

The results from this thesis also help in understanding the successful long-term continuation of the positive trend in the prices of both bitcoin and Gold throughout the pandemic period, as physical movements of people were restricted during the pandemic and the usage of the internet was seen as a great alternative for daily life, making mention of the drastic usage of online education, online monetary transactions, etc. The digital financial world gained more attention during this period. The price of Gold in the short run is mainly determined by the forces coming from demand. In the long run, both the forces of demand and supply set the price of Gold (Sjaastad, 2008). (Bouri et al., 2020;

Dutta et al., 2020; Hussain Shahzad et al., 2020), the supply of Gold is hugely affected by the covid-19, and already, Gold has the capability of providing safe heaven. Therefore, the demand increased, resulting in a rise in prices during the pandemic.

5.1. Recommendations

The results from the study simply highlight that covid-19 pandemic had no significant negative impact on the prices of bitcoin and Gold, but the impact on their respective volumes was different, where the volumes of Gold were significantly affected. However, the volumes of bitcoin were not touched by the covid-19 pandemic. This shows how significant the role of the differences and similarities between bitcoin and Gold plays during the period of an externality like the covid-19 pandemic to the global financial markets. Further research can be conducted with different estimation methods directed to the period of time it may take for the shocks of the pandemic to fully die from the bitcoin and gold markets and the possible aftermaths.

5.2. Directions for Future Research

This area of study can be broadened with further research directed to different financial assets which fall under the same categories, like cryptocurrencies or precious metals, or companies in the stock markets to understand how they perform during an external crisis like the covid-19 pandemic. Also, studies can be done with global financial assets like bitcoin and Gold and other major global external factors like wars, critical political changes in a country, or countries' significant open economies.

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